Year: 2019

Spatial variation of human influences on grassland biomass on the Qinghai-Tibetan plateau

Li, Chengxiu ; de Jong, Rogier ; Schmid, Bernhard ; Wulf, Hendrik ; Schaepman, Michael E

Abstract: An improved understanding of increased human influence on ecosystems is needed for predicting ecosystem processes and sustainable ecosystem management. We studied spatial variation of human influence on grassland ecosystems at two scales across the Qinghai-Tibetan Plateau (QTP), where increased human activities may have led to ecosystem degradation. At the 10 km scale, we mapped human-influenced spatial patterns based on a hypothesis that spatial patterns of biomass that could not be attributed to environmental variables were likely correlated to human activities. In part this hypothesis could be supported via a positive correlation between biomass unexplained by environmental variables and livestock density. At the 500 m scale, using distance to settlements within a radius of 8 km as a proxy of human-influence intensity, we found both negatively human-influenced areas where biomass decreased closer to settlements (regions with higher livestock density) and positively human-influenced areas where biomass increased closer to settlements (regions with lower livestock density). These results suggest complex relationships between livestock grazing and biomass, varying between spatial scales and regions. Grazing may boost biomass production across the whole QTP at the 10 km scale. However, overgrazing may reduce it near settlements at the 500 m scale. Our approach of mapping and understanding human influence on ecosystems at different scales could guide pasture management to protect grassland in vulnerable regions on the QTP and beyond.

DOI: https://doi.org/10.1016/j.scitotenv.2019.01.321

Originally published at:
Li, Chengxiu; de Jong, Rogier; Schmid, Bernhard; Wulf, Hendrik; Schaepman, Michael E (2019). Spatial variation of human influences on grassland biomass on the Qinghai-Tibetan plateau. Science of the Total Environment, 665:678-689.
DOI: https://doi.org/10.1016/j.scitotenv.2019.01.321

Spatial variation of human influences on grassland biomass on the Qinghai-Tibetan Plateau

Chengxiu Li, Rogier de Jong, Bernhard Schmid, Hendrik Wulf and Michael E. Schaepman

Remote Sensing Laboratories, University of Zurich, Winterthurerstrasse 190, CH-8057 Zurich, Switzerland

* Corresponding author: chengxiu.li@geo.uzh.ch

Abstract:

An improved understanding of increased human influence on ecosystems is needed for predicting ecosystem processes and sustainable ecosystem management. We studied spatial variation of human influence on grassland ecosystems at two scales across the Qinghai-Tibetan Plateau (QTP), where increased human activities may have led to ecosystem degradation. At the 10 km scale, we mapped human-influenced spatial patterns based on a hypothesis that spatial patterns of biomass that could not be attributed to environmental variables were likely correlated to human activities. In part this hypothesis could be supported via a positive correlation between biomass unexplained by environmental variables and livestock density. At the 500 m scale, using distance to settlements within a radius of 8 km as a proxy of human-influence intensity, we found both negatively human-influenced areas where biomass decreased closer to settlements (regions with higher livestock density) and positively human-influenced areas where biomass increased closer to settlements (regions with lower livestock density). These results suggest complex relationships between livestock grazing and biomass, varying between spatial scales and regions. Grazing may boost biomass production across the whole QTP at the 10 km scale. However, overgrazing may reduce it near settlements. Our approach of mapping and understanding human influence on ecosystems at different scales could guide pasture management to protect grassland in vulnerable regions on the QTP and beyond.

Keywords —Alpine grasslands, distance to settlements, human influences, livestock density, overgrazing, remote sensing of biomass, spatial-pattern modeling

1. Introduction

More than three-quarters of the terrestrial biosphere has been altered by human activities

(Ellis and Ramankutty, 2008) which has also caused unprecedented changes in many Earth-system processes during the last decades (Chen et al., 2013; Ellis, 2015), including regional and local ecological processes (Ellis and Haff, 2009). It is necessary to understand the consequences of human influence on ecosystems to better explain spatial patterns of ecosystems and their responses to climate and other environmental changes (Ellis, 2015). Ecosystem functioning and services have been most affected in arid and semi-arid areas, where recent degradation has taken place (Chen et al., 2014; Harris, 2010; Wessels et al., 2004). The grassland ecosystems in these areas cover a large portion of the Earths' surface and contain substantial amounts of soil organic carbon. Grassland degradation and land-use changes, including conversion of grassland to cropland, result in a loss of grassland ecosystem carbon stocks (Conant et al., 2017; Guo and Gifford, 2002). This is also the case on the Qinghai-Tibetan Plateau (QTP) (Chen et al., 2013), where vast grassland ecosystems store a large amount of carbon, thus playing a significant role in global carbon cycle (Liu et al., 2016; Ni, 2002).

The grassland ecosystems on the QTP also influence the local (Xu et al., 2009) and even global climate, e.g. by triggering South Asian monsoon activity (Duan and Wu, 2005). In addition, the QTP is the source region of Asia's major rivers (Figure 1), which supply fresh water for a large part of the world's population downstream (Foggin, 2008; Xu et al., 2008). The stability of ecosystems on the QTP is thus not only of regional importance but also of global relevance for water supply, radiation feedbacks and global climatic patterns (Meyer et al., 2013).

The grassland ecosystems on the QTP, characterized by slow plant growth and recovery rate after disturbance (Shang and Long, 2007), are particularly vulnerable to and threatened by pressures from climatic changes and human activities. Degradation of alpine grasslands has indeed been observed on the QTP and led to productivity declines, land desertification and an increase of noxious weeds (Fassnacht et al., 2015; Lehnert et al., 2014a). Such degradation not only damages the livelihoods of local people but also threatens biodiversity and the ecological services of the QTP at large (Harris, 2010). However, the causes of the grassland degradation on the QTP are still unclear and have been related to warming-caused desiccation and permafrost degradation (Harris, 2010; Lehnert et al., 2016) or to increasing human activities (Harris, 2010; P. Wang et al., 2016; Zhaoli et al., 2005).

Increasing human activities may have affect grassland biomass production on the QTP, which is mostly covered by rangeland and livestock grazing as the main land-use type (Chen et al., 2013). Privatization of rangeland and semi-nomadic pastoralism have caused increasing grazing pressure (Harris, 2010; Meyer et al., 2013; Wang et al., 2017) and overgrazing of winter pastures (Harris et al., 2016, 2015; L. Li et al., 2017). Moreover, infrastructure development such as highways and townships, tourism and mining exert increasing pressure on QTP grassland ecosystems (S. Li et al., 2017). Human activities of grassland conservation programs (L. Li et al., 2017) and nature reserve programs (S. Li et al., 2018), however, have been launched to protect ecosystems and secure biodiversity and ecosystem services. All these human activities happened at different areas and scales. For example, livestock grazing is widely spread across the whole QTP whereas the grazing pressure is higher in low areas and near settlements. Construction works are site-based and ecosystem protection programs are widely located in the "Three-Rivers headwater regions" in the southern part of Qinghai province. These human activities indicate that human influences on grassland ecosystems are spatially heterogeneous and scale-dependent.

The various human activities and land-use intensity on the QTP, combined with clear environmental and productivity gradients (Chen et al., 2015), imply that the grasslands respond differently to diverse human activities on the QTP. For example, the different levels of grassland productivity translate into different carrying capacities for livestock (Miehe et al., 2008), indicating different levels of resistance to grazing and different grazing effects (Milchunas et al., 1988). Previous studies involved quantifying human influence on grassland dynamics (Chen et al., 2014; Lehnert et al., 2016; L. Li et al., 2018) and mapping of human-influence intensity on the QTP (S. Li et al., 2017). However, quantifying and mapping spatially heterogeneous human influence on grassland ecosystems has not been done so far, yet this would be key to understand how ecosystems respond to environmental changes and to help distinguishing climatic and anthropogenic contributions to spatial variation in grassland biomass. We aimed to map human-influenced spatial patterns of grassland biomass on the QTP at two spatial scales, i.e. at the 10 km scale across the whole QTP and at the 500 m scale near human settlements.

2. Data

2.1 Observed aboveground biomass

Grassland aboveground biomass was assessed using an empirical model based on Landsat-8 satellite data and field-measured data (C. Li et al., 2018). Vegetation with higher biomass shows stronger reflectance in near-infrared bands but lower reflectance in visible bands than grassland with lower biomass. The Normalized Difference Vegetation Index (NDVI) was developed to characterize the vegetation (Tucker, 1979) and has been extensively used to estimate aboveground grassland biomass (Jia et al., 2016; Zhang et al., 2016). The 172 biomass plots were measured in the field during peak growing season (late July to mid-August) in 2015 and 2016. The closest Landsat-8 NDVI values were extracted with respect to the individual field sampling locations and dates. The field-measured biomass data were randomly split into two parts, using three-quarters of the data for model calibration and one-quarter for validation. The developed empirical model ($R^2 = 0.55$, rRMSE = 0.23) was applied to the Landsat-8 NDVI in 2015 to map grassland biomass with the Google Earth Engine (Gorelick et al., 2017) across the whole QTP.

We rescaled the aboveground biomass map to a spatial resolution of 10 km and 500 m and further mapped human influences on biomass at 10 km and 500 m scale.

2.2 Climatic variables

The climatic variables used to model the contribution of environmental variables to spatial variation in grassland biomass included growing season (June–September) mean air temperature in 2015 and precipitation in 2015. These variables were extracted from the China Meteorological Forcing Dataset with a spatial resolution of 0.1° (Chen et al., 2011). The temperature variable was constructed by merging observations from 740 meteorological stations and corresponding Princeton meteorological forcing data (Sheffield et al., 2006). The precipitation variable was constructed by combining three precipitation data sets, including observations from the same 740 meteorological stations, the Tropical Rainfall Measuring Mission (TRMM) 3B42 precipitation products (Huffman et al., 2007) and the Asian Precipitation-Highly Resolved Observational Data Integration Towards Evaluation of the Water Resources project (APHRODITE) (Yatagai et al., 2009). This climatic dataset has been widely used in soil moisture modeling and ecosystem studies (Guo and Wang, 2013; Liu and Xie, 2013; Wang et al., 2017).

2.3 Soil properties

Soil variables of soil organic matter, available nitrogen and total phosphorus were selected from eight soil variables (available phosphorus, available potassium, available nitrogen, total phosphorus, total potassium, total nitrogen, soil organic matter and soil PH) to estimate aboveground biomass. The selected soil variables have lowest co-linearity (Variance Inflation Factor <10) with other variables (section 3.2). The soil variables were extracted from a 30×30 arcsec resolution gridded soil characteristics dataset (Shangguan et al., 2013). This dataset includes physical and chemical attributes of soils derived from 8979 soil profiles and the Soil Map of China (1:1,000,000). This soil properties dataset has been widely used in soil and ecological studies (Bi et al., 2016; Maire et al., 2015; Sun et al., 2016; Wang et al., 2015).

2.4 Data on eco-geographical regions

The classification of the QTP into eco-geographical regions (Figure 1) was included as a further environmental explanatory variable for spatial variation in grassland biomass (Section 3.1). The eco-geographical regions have been defined based on a combination of climatic factors and vegetation types (Gao et al., 2009). We included the classification of eco-geographical regions as an explanatory variable because it reflects the effects of broad differences in species composition between vegetation types on biomass (Chuang et al., 2014). The eco-region data were converted from a polygon-shape file to a raster with 10 km using the statistical software R (R Core Team, 2018).

2.5 Indicators of human influences

Two indicators of human influence, livestock density and distance to settlements, were used to explain the potentially human-influenced spatial patterns at the 10 km and 500 m scale. The settlement locations of cities, towns, hamlets and villages in 2017 were extracted from OpenStreetMap (Haklay and Weber, 2008) as spatial points (https://download.geofabrik.de/asia/china.html). The size of settlements was considered when analyzing the correlation between biomass and distance to settlements as described below (section 3.2). The Euclidean distance to the closest of these points was calculated for each grid cell of the QTP (Figure 2).

Pasture is the main land-use type on the QTP. Livestock grazing is an important human-influenced activity. Livestock density can serve as an indicator of such human influence. Livestock density was assessed in terms of the number of sheep, goats and yak per square kilometer reported in the 2015 statistical yearbook from Qinghai, Xizang (National Bureau of Statistics of China, 2015). The absolute numbers of different animal species were converted to livestock units using conversion factors of 0.6 for yak and 0.1 for sheep and goats (Lehnert et al., 2016). In the end, livestock densities of 100 counties at the county level were calculated (Figure 2) and decreased from the east to the west of the QTP. The livestock density is suitable to evaluate the human influence on grassland biomass via livestock grazing on the whole QTP scale as demonstrated in previous studies (Lehnert et al., 2016; S. Li et al., 2017). The livestock density data were converted from a polygon shape file to 10 km and 500 m raster in ESRI ArcMap software (http://desktop.arcgis.com/en/arcmap/).

3. Methods

3.1 Model for environmental and human-influenced spatial patterns of biomass at 10 km scale

We hypothesized that the human-influenced biomass could be calculated from the difference between potential biomass in the absence of human activities and actual biomass estimated from the satellite data. This hypothesis and framework is widely used to quantify human contribution on ecosystem biomass production both at the global scale (Haberl et al., 2014, 2007; Krausmann et al., 2013) and at the regional scale of the QTP (Chen et al., 2014; Z. Wang et al., 2016). The potential biomass is the biomass that would be predicted solely by environmental factors without the interference of human activities. Here this potential biomass was defined based on a deterministic empirical model with environmental explanatory variables (x) with regression coefficients β (fixed effects). The actual aboveground biomass, which is influenced by both environmental variables and human activities, was measured from remote sensing NDVI data (y). The difference between potential biomass and actual biomass involves a spatial process (h) that is potentially correlated with human influences (random effects) and a residual noise component ε (Eqn 1) (de Jong et al., 2013). This analysis was conducted at the 10 km scale across the whole QTP by rescaling all environmental explanatory variables to 10 km resolution using the *projectRaster* function in R with bilinear interpolation:

$$h = y - x^T \beta - \varepsilon \qquad (Eqn\ 1)$$

a. Deterministic model (xTβ) attributing biomass to environmental drivers

Temperature, precipitation and soil properties are considered to be the most important variables that may explain spatial biomass variation across the whole QTP (Luo et al., 2004; Sun et al., 2013; Yang et al., 2009). In addition, elevation can account for microclimatic variation and influence grassland biomass (Fisk et al., 1998). Therefore these environmental variables were used to estimate potential biomass.

We used each environmental variable's Variance Inflation Factor (VIF) to quantify co-linearity between variables. VIFs are positive values representing the overall correlation of each predictor with all others in a model. Generally, VIF >10 indicate "severe" co-linearity (Neter et al., 1996; Smith et al., 2009). In the end, six environmental variables including temperature, precipitation, available soil nitrogen, total soil phosphorus, soil organic matter, elevation (Table I) and eco-regions (multi-level factor) were used to develop a multiple linear regression model to predict potential biomass. The VIF of selected environmental variables was 2.4 showing low co-linearity.

A bootstrapping method was applied when estimating model coefficients to avoid spatial dependency in the training data (de Jong et al., 2013). Five thousand samples were randomly selected from 13574 observations to estimate model coefficients. Three-quarter the samples were used for model calibration and one-quarter of samples were used for model validation. This sampling step was repeated five thousand times to include all data into the model. The relative Root-Mean-Square Errors (rRMSEs (%)), that is the ratio between RMSE and the mean of actual biomass, were averaged to estimate model accuracy. Finally, model coefficients were averaged to estimate environmental-driven biomass at the 10 km scale. In addition, to quantify the relative contribution of each variable to biomass, the relative importance of each environmental variables in the multiple linear regressions was investigated using hierarchical variation partitioning as implemented in the R package *relaimpo* (Grömping, 2006) (Table I).

b. Spatial process (*h*) and residuals (ε)

We used a Gaussian random field (GRF) to model the spatial patterns of unexplained effects (de Jong et al., 2013). A GRF is described by three elements: 1) a mean function, 2) a range that determines the length scale of the spatial dependency and 3) a sill that determines the marginal variance. The estimated parameter set was used to model the spatial field h. The detailed description of the model can be found in de Jong et al. (2013). Based on our assumption, the modeled spatial patterns are correlated to human activities. We further tested the spatial patterns (h) for correlations with the human-influenced variable livestock density at the county level.

The residual component ε contains the remaining spatial variation of biomass that was neither captured by the environmental variables (fixed-effects components fitted in the first step) nor by the spatial process (random-effect components fitted in the second step). In the ideal case, these residuals are spatially uncorrelated (de Jong et al., 2013). This component may contain small-scale human interventions (de Jong et al., 2013; Zhou et al., 2001). To find out whether potential small-scale human interventions could be visible, we also related the residuals to the human-influence variable livestock density (county level).

3.2 Model for human-influenced variation of biomass at the 500 m scale

At the 500 m scale, we used distance to settlements as a proxy of human-influence intensity. Distances to watering points or settlements have been widely used as proxies for grazing intensity in various grassland systems with long pastoral histories (Fernandez-Gimenez and Allen-Diaz, 2001; Manthey and Peper, 2010; Wang et al., 2017). On the QTP, the grazing pressure increased over the past three decades near to the settlements because pasture management was transferred from nomadic to semi-nomadic pastoralism or privatized (Meyer et al., 2013; Wang et al., 2017). Therefore, areas closer to settlements experience more intensive human activities, including higher grazing density, construction work and tourism activities.

Human influences on biomass were analyzed within 8-km neighborhoods around settlements at a spatial resolution of 500 m based on previous findings that human influence can be neglected beyond 8 km on the QTP (Liu et al., 2006; Wang et al., 2015). This limit was determined in a breakpoint analysis (see next paragraph). Human activities of grazing, trampling and infrastructure near settlements can directly influence grassland biomass by removal or disturbance, although this may be conterbalanced by compensatory regrowth. Within the range of distances from 0–8 km, a positive correlation between biomass and distance to settlements indicates that biomass is lower near settlements, which suggests a negative human influence on biomass. In contrast, a negative correlation indicates that biomass is higher near settlements, suggesting a positive human influence on biomass. If biomass stays stable along distance to settlements this indicates that human activities do not have a profound influence on biomass. However, beyond the limit distance of 8 km to settlements, the direct human influence on grassland biomass should be small (Liu et al., 2006). Nevertheless, biomass may tend to decrease beyond the limit distance because people avoid areas where potential biomass is low due to harsh environmental conditions (Figure S1). Figure 3 illustrates the above scenarios of changes of biomass along distance to settlements. A supplementary video (supplementary 2) shows examples of changes of biomass along distance to settlements, where a turning point can be observed showing the potential human influential distance and indicating a breakpoint in the relationship between biomass and distance to settlements. The influence of human activities on biomass at the 500 m scale was mapped based on these scenarios.

In order to find the specific human influential distance, the *breakpoints* function and *F* statistics test in the R package strucchange were applied (Zeileis et al., 2003), which have been widely used for detecting and monitoring structural changes in (linear) regression models (Zeileis et al., 2003). We configured the algorithm to detect the one most influential breakpoint for each pixel using a moving-window method. We assumed that the maximum human influential distance could be as large as 15 km, according to the 12 km of human influential distance reported from an area in the east of the QTP (Liu et al., 2006). The detected breakpoint distances were averaged across all pixels to get a single estimate for the entire QTP. This yielded the above-mentioned limit distance of 8 km to settlements beyond which direct human influence related to settlements could no longer be detected (Figure 4).

To detect the spatial variation of human influence on biomass at the 500 m scale, a moving-window method was applied between distance to settlements and biomass. Specifically, we used local Pearson moving-window regression to show positive and negative influences of human activities on biomass. The selected window size with a radius of 8 km for the local Pearson regression was based on the breakpoint analysis explained above. The area covered by settlements has no biomass value and was therefore excluded from the analysis, that is, human influential distance was calculated to the boundary of a settlement, not an inside point. We finally linked the local Pearson correlation coefficients that represent the human-influenced spatial patterns at the 500 m scale with livestock density. Figure 5 summarizes all data and processing steps as a flowchart.

4. Results

4.1 Spatial variation in biomass attributed to environmental drivers at the 10 km scale

The biomass data derived from the Landsat-8 NDVI data showed a decreasing gradient from the east to the west of the QTP and additionally varied strongly within the gradient (Figure 6a). The overall spatial variation in biomass across the QTP was decomposed into three parts: 1) variation explained by environmental variables (Figure 6b), 2) variation due to spatial autocorrelation unexplained by environmental variables but potentially correlated with variation in human influences (Figure 6c and Section 4.2) and 3) residual variation neither explained by environmental variables nor by spatial autocorrelation (Figure S2).

The model developed from environmental variables including climatic variables, soil properties, topographical variables and eco-regions explained 70% (coefficients of determination $R^2 = 0.70$) of the spatial biomass variation with an accuracy of 27% as measured by the rRMSE. The biomass predicted by these environmental variables clearly showed the decreasing trend towards the west described in the previous paragraph. Among different environmental variables, elevation played the most important role in explaining biomass variation, followed by precipitation and soil available nitrogen (Table I). The relatively lower importance of temperature than elevation was probably due to the higher temperature but low biomass in the Qaidam basin, which was opposite to the general trend of decreasing temperature and biomass along increasing elevation (Figure S5).

The biomass predicted by environmental variables shows a sharp transition from high to low biomass along the east-to-west gradient (Figure 6b). This sharp transition was caused by eco-region boundaries and showed the relevance of including eco-regions in the model.

4.2 Spatial variation in biomass potentially due to human-influence at the 10 km scale

The random effects component accounting for spatial autocorrelation in biomass at the 10 km scale, which could not be attributed to variation in environmental variables was potentially related to variation in human influences. This spatial autocorrelation component accounts for 16% of the spatial variation of biomass. Negative spatial autocorrelations in biomass values occurred on the northern part of Qinghai-lake and in the southern part of the QTP. Positive spatial autocorrelations were mainly found in the eastern part of the QTP (Figure 6c). Both the positive and the negative autocorrelations were clearer in the eastern part of the QTP where human activities are more intense (Figure 2 and Figure 6c). A weak positive correlation (R^2 = 0.1) was found between the spatial autocorrelation in biomass and the human-influence variable livestock density (Figure 7). No further correlation was found between residuals and livestock density (Figure S3).

4.3 Human-influenced spatial patterns of biomass at the 500 m scale

The influences of human activities on biomass at the 500 m scale were mapped by analyzing biomass along distance to settlements using a moving window radius of 8 km. The map (Figure 8) shows both biomass decreases and biomass increases near settlements, indicating positive and negative human influences. Strong negative signals were detected in the Yellow River–Huangshui River Valley and around the southeastern part of Qinghai-lake, Xinghai and Tongde counties (Figure 8 (1)), in the Yarlung Zangbo River valley and in the central Tibetan counties of Doilungdeeqeen, Lasa and Dagze (Figure 8 (3)). In all these areas biomass decreased with proximity to settlements. Positive signals were detected for example in the southeastern part of the QTP, i.e. Baima and Jigzhi counties, where the biomass increased with proximity to settlements (Figure 8 (2)).

Across the QTP, positive signals, i.e. higher biomass values closer to settlements, occurred in areas with low livestock density at the 10 km scale. In contrast, the negative signals were correlated with high livestock density, and prevailing negative signals were detected when the regional livestock density was higher than about 22 livestock units per square kilometer (Figure 9), even though these regions are also the ones with more productive ecosystems (Figure S4). In general, biomass was actually larger near settlements in areas with low livestock density, whereas biomass was lower near settlements in more productive areas with higher livestock density.

5. Discussion

5.1 Spatial variation in biomass attributed to environmental drivers at the 10 km scale

The model developed from environmental variables explained most of the spatial variation of biomass (70%). Uncertainties of the model might stem from the limited number of environmental variables used and uncertainties within the environmental variable data, which might affect the potential biomass estimation accuracy. The influence of environmental variables such as soil moisture, soil temperature (X. Wang et al., 2016) and solar radiation (Piao et al., 2006) on biomass has become more important to affect biomass on the QTP under climate change, which should be considered in the future studies. Nevertheless, the environmental variables estimated the potential biomass without the inference of human activities. The difference between the potential biomass and actual biomass are here assumed to be linked with human-influenced variables (Haberl et al., 2007; Pan et al., 2017).

5.2 Human-influenced spatial patterns of biomass at the 10 km scale across the whole QTP

A continuing increase in intensity and diversity of human activities exerts spatially heterogeneous influences on grasslands on the QTP. The spatial patterns of human influence on grassland are unknown on the QTP, which are important to understand how different human activities are impacting the ecosystems and how these respond to environmental change. We mapped spatial patterns at two spatial scales and studied whether the patterns can be explained by livestock grazing density.

At the 10 km scale, we found that livestock density was positively correlated with the human-influenced spatial pattern of grassland biomass, which indicated that at large scale grazing and biomass have a positive relationship. The QTP has served as pastoral land for thousands of years (Klein et al., 2007; Lu et al., 2017). Grassland ecosystems can become adapted to grazing

(Miehe et al., 2009) and major plant species are grazing-resilient (Miehe et al., 2013, 2011). Moderate grazing intensity can promote nutrient recycling and ecosystem production (Lu et al., 2017; Luo et al., 2012). Consistent with these finding, we observed that the potential biomass predicted using only environmental variables was lower than the biomass estimated from the satellite data especially in the eastern part of the QTP, where livestock grazing is the common land use. Appropriate grazing management can affect species composition and facilitate mineral uptake and hydrological processes (Schrama et al., 2013). These effects potentially boost the biomass production, especially in ecosystems that are more productive and more resilient to grazing (Milchunas and Lauenroth, 1993; Wang and Wesche, 2016), which seems to be the case in the eastern and the southeastern part of the QTP (Figure 6c). In summary, positive grazing effects might explain the positive correlation between livestock density and human-influenced spatial patterns in grassland biomass. The opposite causality, i.e. that livestock density is higher where biomass — unexplained by environmental variables — is higher, seems less plausible unless these higher biomass values were caused by unmeasured environmental variables.

Except for livestock grazing effects, other human activities including ongoing ecosystem restoration projects and infrastructure development might explain potential human-influenced spatial pattern in grassland biomass (Fig. 6 (b)). This is especially the case in the eastern and central areas of the QTP because in these areas human activities of land-use changes and grazing density are more widespread and more intense (S. Li et al., 2017), whereas in the northwestern part of the QTP human activities are less widespread and less intense (Figure 2).

5.3 Human-influenced spatial patterns of biomass at the 500 m scale

The mobility of pastoralists has decreased and they have become more sedentary across Africa, Asia, the Middle East and the Americas (Sayre et al., 2017), which leads to increased grazing intensity near settlements (Batjargal, 1997; Vanselow et al., 2012). Distance to settlements could potentially serve as a proxy of human-influence intensity in pastoral ecosystems (Fernandez-Gimenez and Allen-Diaz, 2001; Manthey and Peper, 2010), including the QTP (Wang et al., 2017). Thus, recent studies report that livestock-grazing pressure has been increased around settlements on the QTP (Dorji et al., 2013; Hafner et al., 2012; Lehnert et al., 2014b). Here we analyzed how distance to settlements as a proxy of human-influence intensity correlated with grassland biomass across the entire QTP.

Increased biomass closer to settlements might suggest positive grazing effects, including effects of increased input of nutrients with cattle manure (Lehnert et al., 2014a). On the other hand, implemented ecosystem restoration projects may also contribute to increased biomass near settlements in some areas, for example in the area of south Sanjiangyuan Jigzhi and Baima County, where positive biomass signals close to settlements were observed (Figure 8 (4) and previous studies of Cai et al., 2015; Xu et al., 2011). However, negative biomass signals close to human settlements were observed in the Xinghai and Tongde County in spite of ecosystem restoration projects in these areas (Figure 8 (1)).

Typically, reduced biomass near settlements is taken as an indication of negative human influences due to overgrazing (Hafner et al., 2012). Overgrazing can lead to the reduction of vegetative cover and soil erosion (Papanastasis, 2009; Thornes, 2007), which might be the case in the two regions of the Yarlung Zangbo River valley and the Yellow River-Huangshui River Valley, where we observed negative biomass signals close to human settlements (Figure 8). These regions are characterized by high human population density, livestock-grazing intensity, land use and infrastructure pressure (S. Li et al., 2017). That overgrazing could be one of the main reasons for negative biomass signals near settlements in our study is supported by the fact that these negative signals occurred mainly in areas with high livestock density (Figure 9).

The influence of grazing on ecosystem degradation on the QTP is still a topic of debate. Some studies found that heavy grazing causes severe rangeland degradation or even desertification (Song et al., 2009; Wang et al., 2012), whereas other studies found that grazing improved forage quality and extended the growing season (Chen et al., 2013; Harris, 2010; Klein et al., 2007). In the study, we argue that both situations occur on the QTP, depending on the study area and the study scale. Across the whole QTP, grazing is positively related to biomass production at the 10 km scale. However, because of the limited mobility of local herders (Wang et al., 2017), overgrazing occurs near settlements in areas with high livestock density. The overgrazed area might be more vulnerable and more sensitive to climate change, which requires further attention in future ecosystem protection projects.

However, the changes of biomass with distance to settlements may also be influenced by other, unmeasured human-influence variables than only by grazing intensity and it may furthermore interact with other environmental variables such as soil properties (Papanastasis, 2009). Therefore, the observed spatial patterns need further understanding and validation by combining detailed human activity-indicators with environmental variables. In addition, our study is a single snapshot in time, assessing the human-influenced spatial patterns in grassland biomass in 2015. Future studies should also assess changes over time in these human-influenced spatial patterns.

6. Conclusions

Increased human-influenced activities including livestock grazing and township development exert spatially complex influences on grassland biomass on the QTP. Our study on spatial variation of human influences on grassland biomass on the QTP helps us to understand how these ecosystems may respond to environmental change. At the 10 km scale across the whole QTP we estimated spatial variation of human-influenced biomass by measuring the difference between the potential aboveground biomass without the interference of human actives and actual biomass estimated from the remote sensing data. We found both positive and negative human-influenced spatial patterns across the whole QTP. These patterns positively linked to the livestock density at the county level. At the 500 m scale, we analyzed the human influence on grassland biomass as a function of distance to settlements, used as a proxy of human-influence intensity. This was done because the socioeconomic changes of privatization of pasture land and of sedentarization of nomadic herders was assumed to have increased livestock grazing and other pressures near settlements. We detected hotspots where the biomass decreased or increased towards settlements within a radius of 8 km, indicating both negative and positive human influences on biomass. In particular, we found that biomass decreased near settlements in areas with high livestock density at county level. Overall, our study showed both positive and negative human influences on grassland biomass at two spatial scales, demonstrating the complexity of the relationship between human-influence intensity and grassland biomass, leading to large spatial variation in the relationship across the entire QTP. As a broad generalization we conclude that livestock grazing so far had positive effects on grassland biomass across the whole QTP but overgrazing near settlements now represents a threat to the future biomass production and stability of these ecosystems.

7. Acknowledgements

The forcing climatic dataset used in this study was developed by Data Assimilation and Modeling Center for Tibetan Multi-spheres, Institute of Tibetan Plateau Research, Chinese Academy of Sciences. We acknowledge the OpenStreetMap for providing settlements spatial data. Chengxiu Li was funded by the Chinese Scholarship Council (CSC). This study was conducted in the framework of the University of Zurich Research Program on Global Change and Biodiversity (URPP GCB).

Reference

Batjargal, Z., 1997. Desertification in Mongolia. RALA Rep. No. 200 7.

Cai, H., Yang, X., Xu, X., 2015. Human-induced grassland degradation/restoration in the central Tibetan Plateau: The effects of ecological protection and restoration projects. Ecol. Eng. 83, 112–119. doi:10.1016/j.ecoleng.2015.06.031

Chen, B., Zhang, X., Tao, J., Wu, J., Wang, J., Shi, P., Zhang, Y., Yu, C., 2014. The impact of climate change and anthropogenic activities on alpine grassland over the Qinghai-Tibet Plateau. Agric. For. Meteorol. 189–190, 11–18. doi:10.1016/j.agrformet.2014.01.002

Chen, H., Zhu, Q., Peng, C., Wu, N., Wang, Y., Fang, X., Gao, Y., Zhu, D., Yang, G., Tian, J., Kang, X., Piao, S., Ouyang, H., Xiang, W., Luo, Z., Jiang, H., Song, X., Zhang, Y., Yu, G., Zhao, X., Gong, P., Yao, T., Wu, J., 2013. The impacts of climate change and human activities on biogeochemical cycles on the Qinghai-Tibetan Plateau. Glob. Chang. Biol. 19, 2940–2955. doi:10.1111/gcb.12277

Chen, X., An, S., Inouye, D.W., Schwartz, M.D., 2015. Temperature and snowfall trigger alpine vegetation green-up on the world's roof. Glob. Chang. Biol. 21, 3635–3646. doi:10.1111/gcb.12954

Chen, Y., Yang, K., He, J., Qin, J., Shi, J., Du, J., He, Q., 2011. Improving land surface temperature modeling for dry land of China. J. Geophys. Res. Atmos. 116, 1–15. doi:10.1029/2011JD015921

Chuang, L., Ruixiang, S., Wenbo, C., 2014. Eco-regional boundary data of the Roof of the World. Acta Geogr. Sin. 69, 140–143. doi:10.3974/Global

Conant, R.T., Cerri, C.E.P., Osborne, B.B., Paustian, K., 2017. Grassland management impacts on soil carbon stocks: a new synthesis. Ecol. Appl. 27, 662–668. doi:10.1002/eap.1473

de Jong, R., Schaepman, M.E., Furrer, R., de Bruin, S., Verburg, P.H., 2013. Spatial relationship between climatologies and changes in global vegetation activity. Glob. Chang. Biol. 19, 1953–1964. doi:10.1111/gcb.12193

Dorji, T., Totland, Ø., Moe, S.R., 2013. Are droppings, distance from pastoralist camps, and pika burrows good proxies for local grazing pressure? Rangel. Ecol. Manag. 66, 26–33. doi:10.2111/REM-D-12-00014.1

Duan, A.M., Wu, G.X., 2005. Role of the Tibetan Plateau thermal forcing in the summer climate patterns over subtropical Asia. Clim. Dyn. 24, 793–807. doi:10.1007/s00382-004-0488-8

Ellis, E.C., 2015. Ecology in an anthropogenic biosphere. Ecol. Monogr. 85, 287–331. doi:10.1890/14-2274.1

Ellis, E.C., Haff, P.K., 2009. Earth science in the anthropocene: New Epoch, new Paradigm, new responsibilities. Eos (Washington. DC). 90, 473. doi:10.1029/2009EO490006

Ellis, E.C., Ramankutty, N., 2008. Putting people in the map: Anthropogenic biomes of the world. Front. Ecol. Environ. 6, 439–447. doi:10.1890/070062

Farr, T., Rosen, P., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., Alsdorf, D., 2007. The shuttle radar topography mission. Rev. Geophys. 45, 1–33. doi:10.1029/2005RG000183.1.INTRODUCTION

Fassnacht, F.E., Li, L., Fritz, A., 2015. Mapping degraded grassland on the Eastern Tibetan Plateau with multi-temporal Landsat 8 data - where do the severely degraded areas occur? Int. J. Appl. Earth Obs. Geoinf. 42, 115–127. doi:10.1016/j.jag.2015.06.005

Fernandez-Gimenez, M., Allen-Diaz, B., 2001. Vegetation change along gradients from water sources in three grazed Mongolian ecosystems. Plant Ecol. 157, 101–118. doi:10.1023/A:1014519206041

Fisk, M.C., Schmidt, S.K., Seastedt, T.R., 1998. Topographic patterns of above- and belowground poduction and nitrogen cycling in alpine tundra. Ecology 79, 2253–2266. doi:10.1890/0012-9658(1998)079[2253:TPOAAB]2.0.CO;2

Foggin, J.M., 2008. Depopulating the Tibetan Grasslands. Mt. Res. Dev. 28, 26–31. doi:10.1659/mrd.0972

Gao, J., Li, S., Zhao, Z., 2009. Validating the demarcation of eco-geographical regions: A geostatistical application. Environ. Earth Sci. 59, 1327–1336. doi:10.1007/s12665-009-0120-7

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ. doi:10.1016/j.rse.2017.06.031

Grömping, U., 2006. Relative importance for linear regression in R: the package relaimpo. J. Stat. Softw. 17, 139–147. doi:10.1016/j.foreco.2006.08.245

Guo, D., Wang, H., 2013. Simulation of permafrost and seasonally frozen ground conditions on the Tibetan Plateau, 1981-2010. J. Geophys. Res. Atmos. 118, 5216–5230. doi:10.1002/jgrd.50457

Guo, L.B., Gifford, R.M., 2002. Soil carbon stocks and land use change: A meta analysis. Glob. Chang. Biol. 8, 345–360. doi:10.1046/j.1354-1013.2002.00486.x

Haberl, H., Erb, K.-H., Krausmann, F., 2014. Human Appropriation of Net Primary Production: Patterns, Trends, and Planetary Boundaries. Annu. Rev. Environ. Resour. 39, 363–391. doi:10.1146/annurev-environ-121912-094620

Haberl, H., Erb, K.H., Krausmann, F., Gaube, V., Bondeau, A., Plutzar, C., Gingrich, S., Lucht, W., Fischer-Kowalski, M., 2007. Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. Proc. Natl. Acad. Sci. 104, 12942–12947. doi:10.1073/pnas.0704243104

Hafner, S., Unteregelsbacher, S., Seeber, E., Lena, B., 2012. Effect of grazing on carbon stocks and assimilate partitioning in a Tibetan montane pasture revealed by 13 CO 2 pulse labeling 528–538. doi:10.1111/j.1365-2486.2011.02557.x

Haklay, M., Weber, P., 2008. OpenStreet map: User-generated street maps. IEEE Pervasive Comput. 7, 12–18. doi:10.1109/MPRV.2008.80

Harris, R.B., 2010. Rangeland degradation on the Qinghai-Tibetan plateau: A review of the evidence of its magnitude and causes. J. Arid Environ. 74, 1–12. doi:10.1016/j.jaridenv.2009.06.014

Harris, R.B., Samberg, L.H., Yeh, E.T., Smith, A.T., Wenying, W., Junbang, W., Gaerrang, Bedunah, T.L.D.J., 2016. Rangeland responses to pastoralists' grazing management on a Tibetan steppe grassland, Qinghai Province, China. Rangel. J. 38, 1–15. doi:10.1071/RJ15040

Harris, R.B., Wenying, W., Badinqiuying, Smith, A.T., Bedunah, D.J., 2015. Herbivory and competition of Tibetan steppe vegetation in winter pasture: Effects of livestock exclosure and plateau pika reduction. PLoS One 10. doi:10.1371/journal.pone.0132897

Huffman, G.J., Bolvin, D.T., Nelkin, E.J., Wolff, D.B., Adler, R.F., Gu, G., Hong, Y., Bowman, K.P., Stocker, E.F., 2007. The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales. J. Hydrometeorol. 8, 38–55. doi:10.1175/JHM560.1

Jia, W., Liu, M., Yang, Y., He, H., Zhu, X., Yang, F., Yin, C., Xiang, W., 2016. Estimation and uncertainty analyses of grassland biomass in Northern China: Comparison of multiple remote sensing data sources and modeling approaches. Ecol. Indic. 60, 1031–1040. doi:10.1016/j.ecolind.2015.09.001

Klein, J.A., Harte, J., Zhao, X.Q., 2007. Experimental warming, not grazing, decreases rangeland quality on the Tibetan Plateau. Ecol. Appl. 17, 541–557. doi:10.1890/05-0685

Krausmann, F., Erb, K.-H., Gingrich, S., Haberl, H., Bondeau, A., Gaube, V., Lauk, C., Plutzar, C., Searchinger, T.D., 2013. Global human appropriation of net primary production doubled in the 20th century. Proc. Natl. Acad. Sci. 110, 10324–10329.

doi:10.1073/pnas.1211349110

Lehnert, L.W., Meyer, H., Meyer, N., Reudenbach, C., Bendix, J., 2014a. A hyperspectral indicator system for rangeland degradation on the Tibetan Plateau: A case study towards spaceborne monitoring. Ecol. Indic. 39, 54–64. doi:10.1016/j.ecolind.2013.12.005

Lehnert, L.W., Meyer, H., Meyer, N., Reudenbach, C., Bendix, J., 2014b. A hyperspectral indicator system for rangeland degradation on the Tibetan Plateau: A case study towards spaceborne monitoring. Ecol. Indic. 39, 54–64. doi:10.1016/j.ecolind.2013.12.005

Lehnert, L.W., Wesche, K., Trachte, K., Reudenbach, C., Bendix, J., 2016. Climate variability rather than overstocking causes recent large scale cover changes of Tibetan pastures. Sci. Rep. 6, 24367. doi:10.1038/srep24367

Li, C., Wulf, H., Schmid, B., He, J., Schaepman, M.E., Member, S., 2018. Estimating Plant Traits of Alpine Grasslands on the Qinghai-Tibetan Plateau Using Remote Sensing 1–13.

Li, L., Fassnacht, F.E., Storch, I., B??rgi, M., 2017. Land-use regime shift triggered the recent degradation of alpine pastures in Nyanpo Yutse of the eastern Qinghai-Tibetan Plateau. Landsc. Ecol. 1–17. doi:10.1007/s10980-017-0510-2

Li, L., Zhang, Y., Liu, L., Wu, J., Li, S., Zhang, H., Zhang, B., Ding, M., Wang, Z., Paudel, B., 2018. Current challenges in distinguishing climatic and anthropogenic contributions to alpine grassland variation on the Tibetan Plateau. Ecol. Evol. 8, 5949–5963. doi:10.1002/ece3.4099

Li, S., Wu, J., Gong, J., Li, S., 2018. Human footprint in Tibet: Assessing the spatial layout and effectiveness of nature reserves. Sci. Total Environ. 621, 18–29. doi:10.1016/j.scitotenv.2017.11.216

Li, S., Zhang, Y., Wang, Z., Li, L., 2017. Mapping human influence intensity in the Tibetan Plateau for conservation of ecological service functions. Ecosyst. Serv.

doi:10.1016/j.ecoser.2017.10.003

Liu, J.G., Xie, Z.H., 2013. Improving simulation of soil moisture in China using a multiple meteorological forcing ensemble approach. Hydrol. Earth Syst. Sci. 17, 3355–3369. doi:10.5194/hess-17-3355-2013

Liu, L., Zhang, Y., Bai, W., Yan, J., Ding, M., Shen, Z., Li, S., Zheng, D., 2006. Characteristics of grassland degradation and driving forces in the source region of the Yellow River from 1985 to 2000. J. Geogr. Sci. 16, 131–142. doi:10.1007/s11442-006-0201-4

Liu, S., Zhang, F., Du, Y., Guo, X., Lin, L., Li, Y., Li, Q., Cao, G., 2016. Ecosystem carbon storage in alpine grassland on the Qinghai Plateau. PLoS One 11, e0160420. doi:10.1371/journal.pone.0160420

Lu, X., Kelsey, K.C., Yan, Y., Sun, J., Wang, X., Cheng, G., Neff, J.C., 2017. Effects of grazing on ecosystem structure and function of alpine grasslands in Qinghai-Tibetan Plateau: A synthesis. Ecosphere 8. doi:10.1002/ecs2.1656

Luo, G., Han, Q., Zhou, D., Li, L., Chen, X., Li, Y., Hu, Y., Li, B.L., 2012. Moderate grazing can promote aboveground primary production of grassland under water stress 11, 126–136. doi:10.1016/j.ecocom.2012.04.004

Luo, T., Pan, Y., Ouyang, H., Shi, P., Luo, J., Yu, Z., Lu, Q., 2004. Leaf area index and net primary productivity along subtropical to alpine gradients in the Tibetan Plateau. Glob. Ecol. Biogeogr. 13, 345–358. doi:10.1111/j.1466-822X.2004.00094.x

Manthey, M., Peper, J., 2010. Estimation of grazing intensity along grazing gradients - the bias of nonlinearity. J. Arid Environ. 74, 1351–1354. doi:10.1016/j.jaridenv.2010.05.007

Meyer, H., Lehnert, L.W., Wang, Y., Reudenbach, C., Bendix, J., 2013. Measuring pasture degradation on the Qinghai-Tibet Plateau using hyperspectral dissimilarities and indices.

Proc. SPIE 8893, 88931F–88931F–13. doi:10.1117/12.2028762

Miehe, G., Miehe, S., Bach, K., Nölling, J., Hanspach, J., Reudenbach, C., Kaiser, K., Wesche, K., Mosbrugger, V., Yang, Y.P., Ma, Y.M., 2011. Plant communities of central Tibetan pastures in the Alpine Steppe/Kobresia pygmaea ecotone. J. Arid Environ. 75, 711–723. doi:10.1016/j.jaridenv.2011.03.001

Miehe, G., Miehe, S., Bach, K., Wesche, K., Seeber, E., Behrendes, L., Kaiser, K., Reudenbach, C., Nölling, J., Hanspach, J., Herrmann, M., Yaoming, M., Mosbrugger, V., 2013. Resilience or vulnerability? Vegetation patterns of a Central Tibetan pastoral ecotone. Steppe Ecosyst. Biol. Divers. Manag. Restor. 111–151.

Miehe, G., Miehe, S., Kaiser, K., Liu, J., Zhao, X., 2008. Status and dynamics of the Kobresia pygmaea ecosystem on the Tibetan plateau. Ambio 37, 272–279. doi:10.1579/0044-7447(2008)37[272:SADOTK]2.0.CO;2

Miehe, G., Miehe, S., Kaiser, K., Reudenbach, C., Behrendes, L., La Duo, Schlütz, F., 2009. How old is pastoralism in Tibet? An ecological approach to the making of a Tibetan landscape. Palaeogeogr. Palaeoclimatol. Palaeoecol. 276, 130–147. doi:10.1016/j.palaeo.2009.03.005

Milchunas, D.G., Lauenroth, W.K., 1993. Quantitative effects of grazing on vegetation and soils over a global range of environmnents. Ecol. Monogr. 63, 327–366. doi:10.2307/2937150

Milchunas, D.G., Sala, O.E., Lauenroth, W.K., 1988. A Generalized Model of the Effects of Grazing by Large Herbivores on Grassland Community Structure. Am. Nat. 132, 87–106.

National Bureau of Statistics of China, 2015. China STATISTICAL YEARBOOK 2015. China Statistical Press, Beijing.

Neter, J., Kutner, M.H., Nachtsheim, C.J., Wasseman, W., 1996. Applied Linear Statistical

Models, 4th ed. McGraw-Hill.

Ni, J., 2002. Carbon storage in grasslands of China. J. Arid Environ. 50, 205–218. doi:10.1006/jare.2001.0902

Pan, T., Zou, X., Liu, Y., Wu, S., He, G., 2017. Contributions of climatic and non-climatic drivers to grassland variations on the Tibetan Plateau. Ecol. Eng. 108, 307–317. doi:10.1016/j.ecoleng.2017.07.039

Papanastasis, V.P., 2009. Restoration of degraded grazing lands through grazing management: Can it work? Restor. Ecol. 17, 441–445. doi:10.1111/j.1526-100X.2009.00567.x

Piao, S., Fang, J., Jinsheng, H.E., 2006. Variations in vegetation net primary production in the Qinghai-Xizang Plateau, China, from 1982 to 1999. Clim. Change 74, 253–267. doi:10.1007/s10584-005-6339-8

Pugnaire, F.I., Zhang, L., Li, R., Luo, T., 2015. No evidence of facilitation collapse in the Tibetan plateau. J. Veg. Sci. 26, 233–242. doi:10.1111/jvs.12233

R Core Team, 2018. R: A language and environment for statistical computing. R Found. Stat. Comput. Vienna, Austria.

Sayre, N.F., Davis, D.K., Bestelmeyer, B., Williamson, J.C., 2017. Rangelands: Where Anthromes Meet Their Limits. Land 6, 31. doi:10.3390/land6020031

Schrama, M., Veen, G.F.C., Bakker, E.S.L., Ruifrok, J.L., Bakker, J.P., Olff, H., 2013. An integrated perspective to explain nitrogen mineralization in grazed ecosystems. Perspect. Plant Ecol. Evol. Syst. 15, 32–44. doi:10.1016/j.ppees.2012.12.001

Shang, Z., Long, R., 2007. Formation causes and recovery of the “black Soil Type” degraded alpine grassland in Qinghai-Tibetan Plateau. Front. Agric. China 1, 197–202. doi:10.1007/s11703-007-0034-7

Shangguan, W., Dai, Y., Liu, B., Zhu, A., Duan, Q., Wu, L., Ji, D., Ye, A., Yuan, H., Zhang, Q., Chen, D., Chen, M., Chu, J., Dou, Y., Guo, J., Li, H., Li, J., Liang, L., Liang, X., Liu, H., Liu, S., Miao, C., Zhang, Y., 2013. A China data set of soil properties for land surface modeling. J. Adv. Model. Earth Syst. 5, 212–224. doi:10.1002/jame.20026

Smith, A.C., Koper, N., Francis, C.M., Fahrig, L., 2009. Confronting collinearity: Comparing methods for disentangling the effects of habitat loss and fragmentation. Landsc. Ecol. 24, 1271–1285. doi:10.1007/s10980-009-9383-3

Song, X., Yang, G., Yan, C., Duan, H., Liu, G., Zhu, Y., 2009. Driving forces behind land use and cover change in the Qinghai-Tibetan Plateau: A case study of the source region of the Yellow River, Qinghai Province, China. Environ. Earth Sci. 59, 793–801. doi:10.1007/s12665-009-0075-8

Sun, J., Cheng, G.W., Li, W.P., 2013. Meta-analysis of relationships between environmental factors and aboveground biomass in the alpine grassland on the Tibetan Plateau. Biogeosciences 10, 1707–1715. doi:10.5194/bg-10-1707-2013

Thornes, J.B., 2007. Modelling soil erosion by grazing: Recent developments and new approaches. Geogr. Res. 45, 13–26. doi:10.1111/j.1745-5871.2007.00426.x

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens. Environ. 8, 127–150. doi:10.1016/0034-4257(79)90013-0

Vanselow, K.A., Kraudzun, T., Samimi, C., 2012. Grazing Practices and Pasture Tenure in the Eastern Pamirs. Mt. Res. Dev. 32, 324–336. doi:10.1659/MRD-JOURNAL-D-12-00001.1

Wang, P., Lassoie, J.P., Morreale, S.J., Dong, S., 2015. A critical review of socioeconomic and natural factors in ecological degradation on the Qinghai-Tibetan Plateau, China. Rangel. J. 37, 1–9. doi:10.1071/RJ14094

Wang, P., Wolf, S.A., Lassoie, J.P., Poe, G.L., Morreale, S.J., Su, X., Dong, S., 2016. Promise and reality of market-based environmental policy in China: Empirical analyses of the ecological restoration program on the Qinghai-Tibetan Plateau. Glob. Environ. Chang. 39, 35–44. doi:10.1016/j.gloenvcha.2016.04.004

Wang, S., Duan, J., Xu, G., Wang, Y., Zhang, Z., Rui, Y., Luo, C., Xu, B., Zhu, X., Chang, X., Cui, X., Niu, H., Zhao, X., Wang, W., 2012. Effects of warming and grazing on soil N availability, species composition, and ANPP in an alpine meadow. Ecology 93, 2365–2376. doi:10.1890/11-1408.1

Wang, X., Yi, S., Wu, Q., Yang, K., Ding, Y., 2016. The role of permafrost and soil water in distribution of alpine grassland and its NDVI dynamics on the Qinghai-Tibetan Plateau. Glob. Planet. Change 147, 40–53. doi:10.1016/j.gloplacha.2016.10.014

Wang, Y., Heberling, G., Görzen, E., Miehe, G., Seeber, E., Wesche, K., 2017. Combined effects of livestock grazing and abiotic environment on vegetation and soils of grasslands across Tibet. Appl. Veg. Sci. 20, 327–339. doi:10.1111/avsc.12312

Wang, Y., Wesche, K., 2016. Vegetation and soil responses to livestock grazing in Central Asian grasslands: a review of Chinese literature. Biodivers. Conserv. 25, 2401–2420. doi:10.1007/s10531-015-1034-1

Wang, Z., Zhang, Y., Yang, Y., Zhou, W., Gang, C., Zhang, Y., Li, J., An, R., Wang, K., Odeh, I., Qi, J., 2016. Quantitative assess the driving forces on the grassland degradation in the Qinghai-Tibet Plateau, in China. Ecol. Inform. 33, 32–44. doi:10.1016/j.ecoinf.2016.03.006

Wessels, K.J., Prince, S.D., Frost, P.E., Van Zyl, D., 2004. Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. Remote Sens. Environ. 91, 47–67. doi:10.1016/j.rse.2004.02.005

Xu, J., Grumbine, R.E., Shrestha, A., Eriksson, M., Yang, X., Wang, Y., Wilkes, A., 2009. The melting Himalayas: Cascading effects of climate change on water, biodiversity, and livelihoods. Conserv. Biol. 23, 520–530. doi:10.1111/j.1523-1739.2009.01237.x

Xu, W., Gu, S., Zhao, X., Xiao, J., Tang, Y., Fang, J., Zhang, J., Jiang, S., 2011. High positive correlation between soil temperature and NDVI from 1982 to 2006 in alpine meadow of the Three-River Source Region on the Qinghai-Tibetan Plateau. Int. J. Appl. Earth Obs. Geoinf. 13, 528–535. doi:10.1016/j.jag.2011.02.001

Xu, X., Lu, C., Shi, X., Gao, S., 2008. World water tower: An atmospheric perspective. Geophys. Res. Lett. 35, 1–5. doi:10.1029/2008GL035867

Yang, Y.H., Fang, J.Y., Pan, Y.D., Ji, C.J., 2009. Aboveground biomass in Tibetan grasslands. J. Arid Environ. 73, 91–95. doi:10.1016/j.jaridenv.2008.09.027

Yatagai, A., Arakawa, O., Kamiguchi, K., Kawamoto, H., 2009. A 44-Year Daily Gridded Precipitation Dataset for Asia. Sola 5, 3–6. doi:10.2151/sola.2009

Zeileis, A., Kleiber, C., Walter, K., Hornik, K., 2003. Testing and dating of structural changes in practice. Comput. Stat. Data Anal. 44, 109–123. doi:10.1016/S0167-9473(03)00030-6

Zhang, B., Zhang, L., Xie, D., Yin, X., Liu, C., Liu, G., 2016. Application of synthetic NDVI time series blended from landsat and MODIS data for grassland biomass estimation. Remote Sens. 8, 10. doi:10.3390/rs8010010

Zhaoli, Y., Ning, W., Dorji, Y., Jia, R., 2005. A REVIEW OF RANGELAND PRIVATISATION AND ITS IMPLICATIONS IN THE TIBETAN PLATEAU, CHINA. Nomad. People. 9, 31–51.

Zhou, L., Tucker, C.J., Kaufmann, R.K., Slayback, D., Shabanov, N. V., Myneni, R.B., 2001. Variations in northern vegetation activity inferred from satellite data of vegetation index during 1981 to 1999. J. Geophys. Res. Atmos. 106, 20069–20083. doi:10.1029/2000JD000115

Table I. Environmental variable's Variance Inflation Factor (VIF) and their relative importance for explaining biomass

Parameter	Unit	VIF	Relative importance
Elevation	m	3.95	0.32
Precipitation	mm	2.59	0.23
Available N	g/100g	2.78	0.23
Soil organic matter	g/100g	2.62	0.13
Temperature	℃	2.30	0.06
Total P	g/100g	1.57	0.03

Figure 1. Distribution of main grassland vegetation types, eco-regions and major rivers (with names) on the Qinghai-Tibetan Plateau (QTP). Inset indicates elevation data of the extended area based on the NASA Shuttle Radar Topographic Mission (SRTM Version 4; Farr et al., 2007).

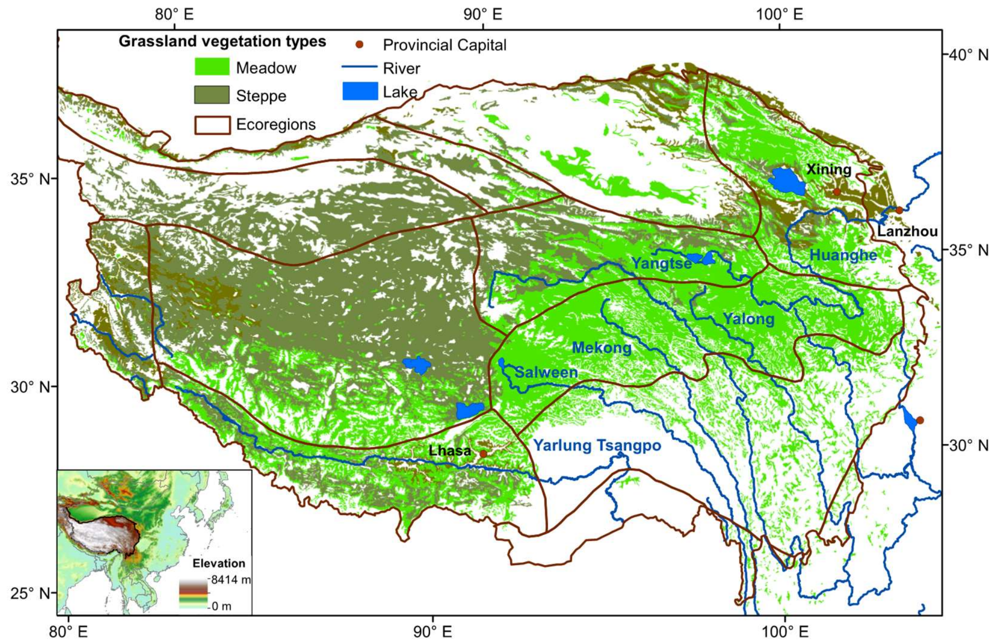

Figure 2. Livestock density at county level and distance to settlements at the 500 m scale on the Qinghai-Tibetan Plateau.

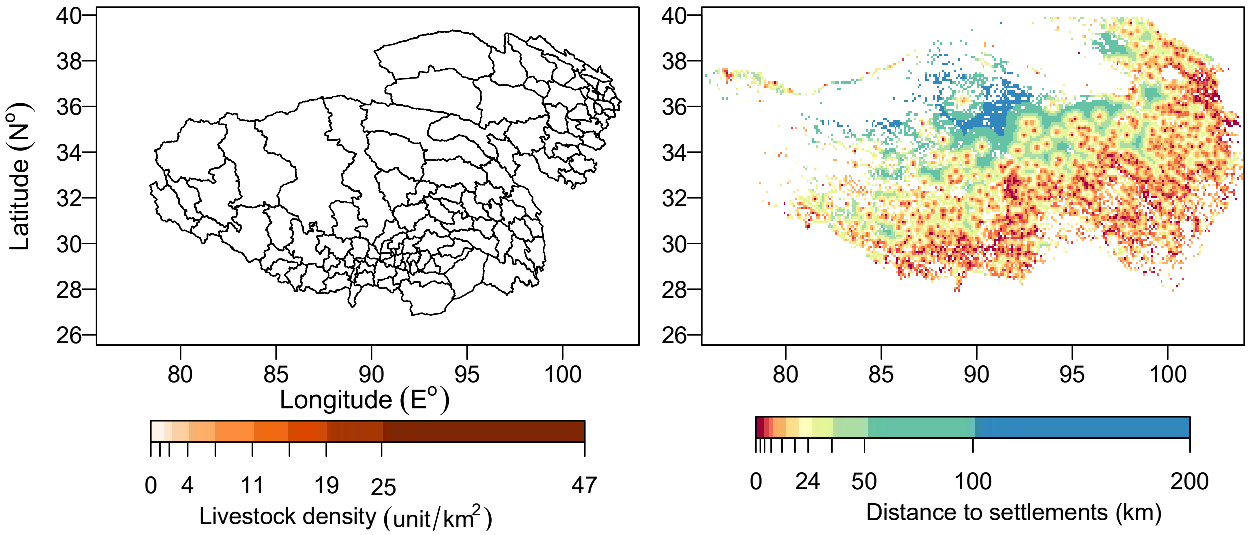

Figure 3. Three scenarios of relationships between distance to settlements and grassland biomass: 1 (orange) – biomass decreases near settlements potentially showing a negative human influence on biomass, 2 (blue) – no clear human influence on biomass and 3 (green) – biomass increases near settlements suggesting a positive human influence on biomass. All scenarios hold up to a certain distance (8 km) after which the relationship between biomass and distance tends to be negative (see Figure S1).

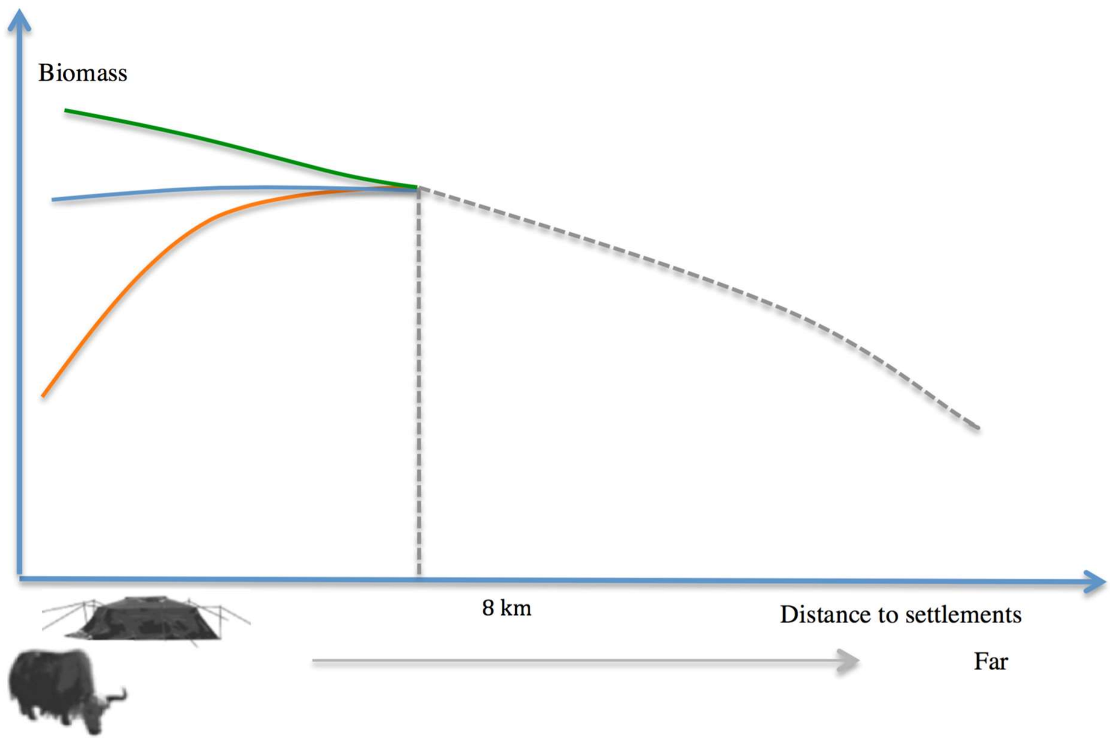

Figure 4. The human influential distances on the Qinghai-Tibetan Plateau (a) and their distribution (b). The distances were calculated for local areas using *breakpoints* analysis in R (see Methods). The histogram shows that the average human influential distance is about 8 km.

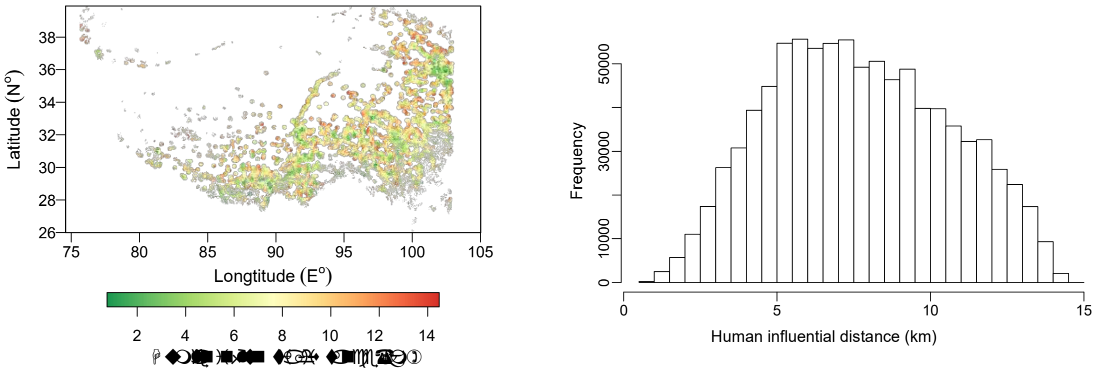

Figure 5. Flowchart displaying data and methods used to map the influence of human activities on biomass at 10 km ("Regional") and 500 m ("Local") scales.

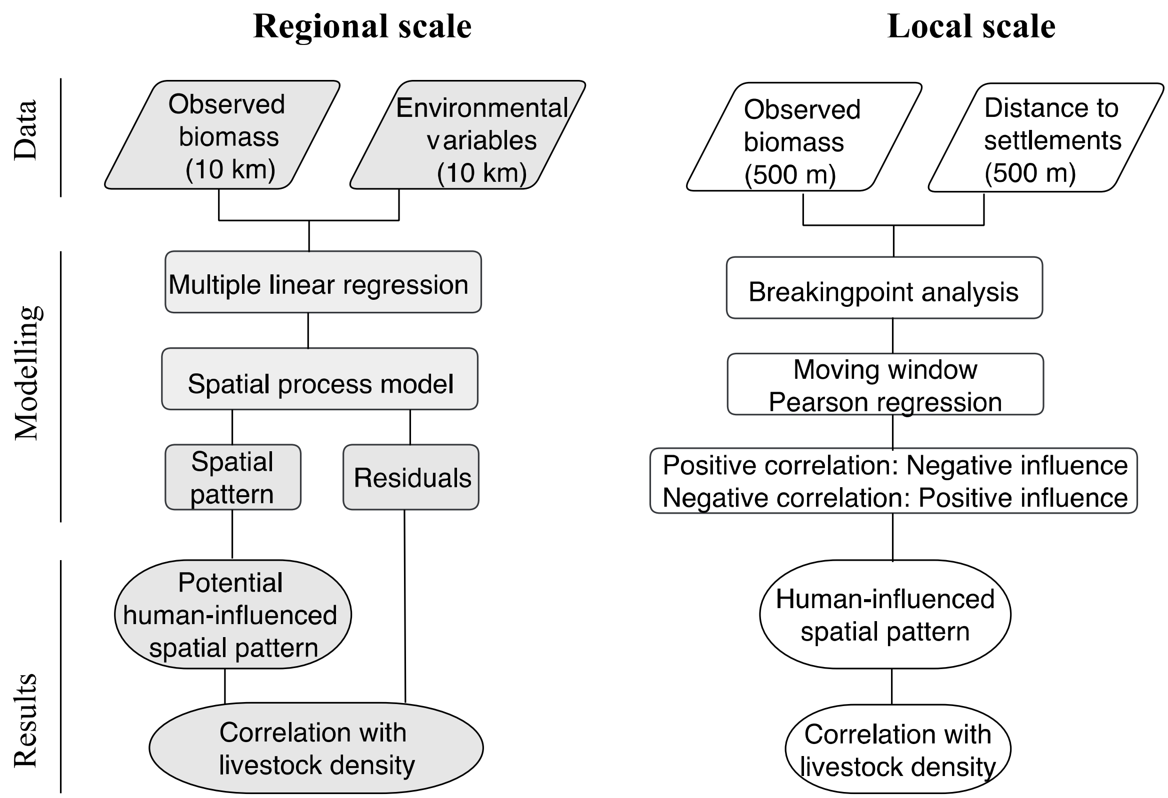

Figure 6. Observed biomass using Landsat-8 NDVI vegetation index (a). Biomass predicted using environmental variables (b). Spatial autocorrelation of biomass that could not be explained by environmental variables but possibly human-influence variables (c). Positive hotspots of human influences are indicated with numbers. The circle represents a positive hotspot with a positive human influence at the 500 m scale (Figure 7), whereas the two squares represent positive hotspots with a negative human influence at the 500 m scale.

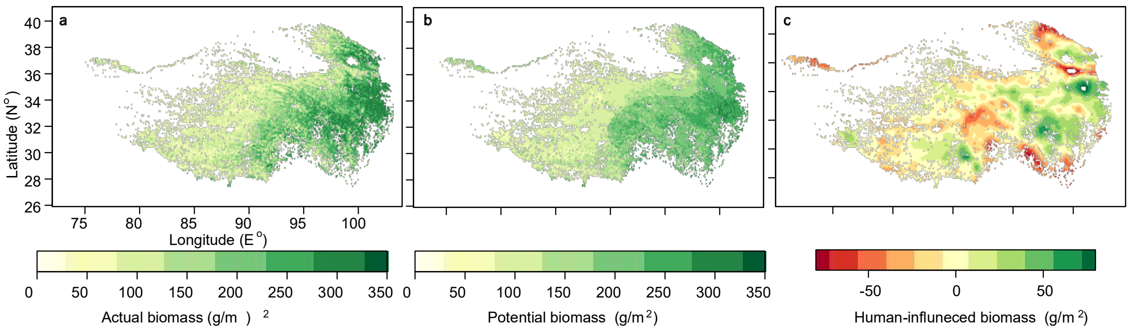

Figure 7. Scatterplot between human-influenced spatial pattern of grassland biomass (y) and livestock density (x).

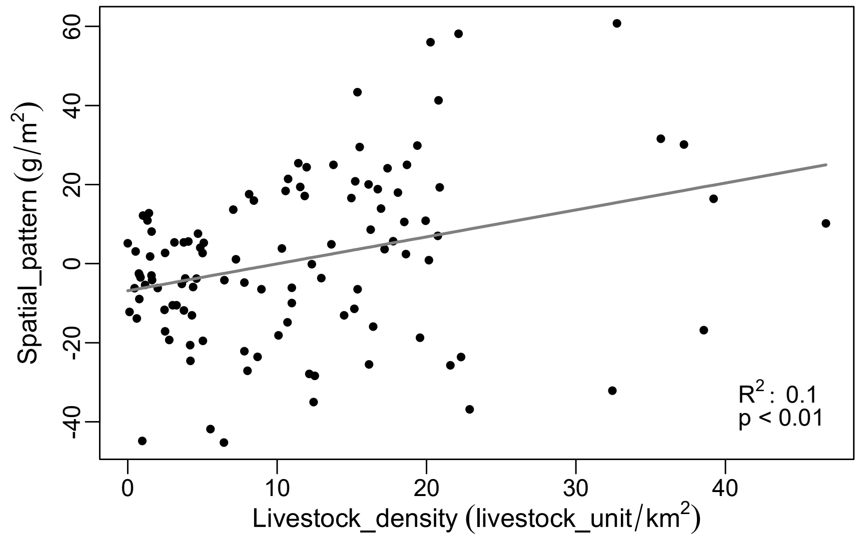

Figure 8. Correlation coefficients between biomass and distance to settlements (within 8 km) at grid cells of 500 m × 500 m (top left panel). A positive correlation shows biomass decreases near settlements and indicates negative human influences and vise versa. Some hotspots of negative and positive human influences area are shown in panels (1), (2), (4).

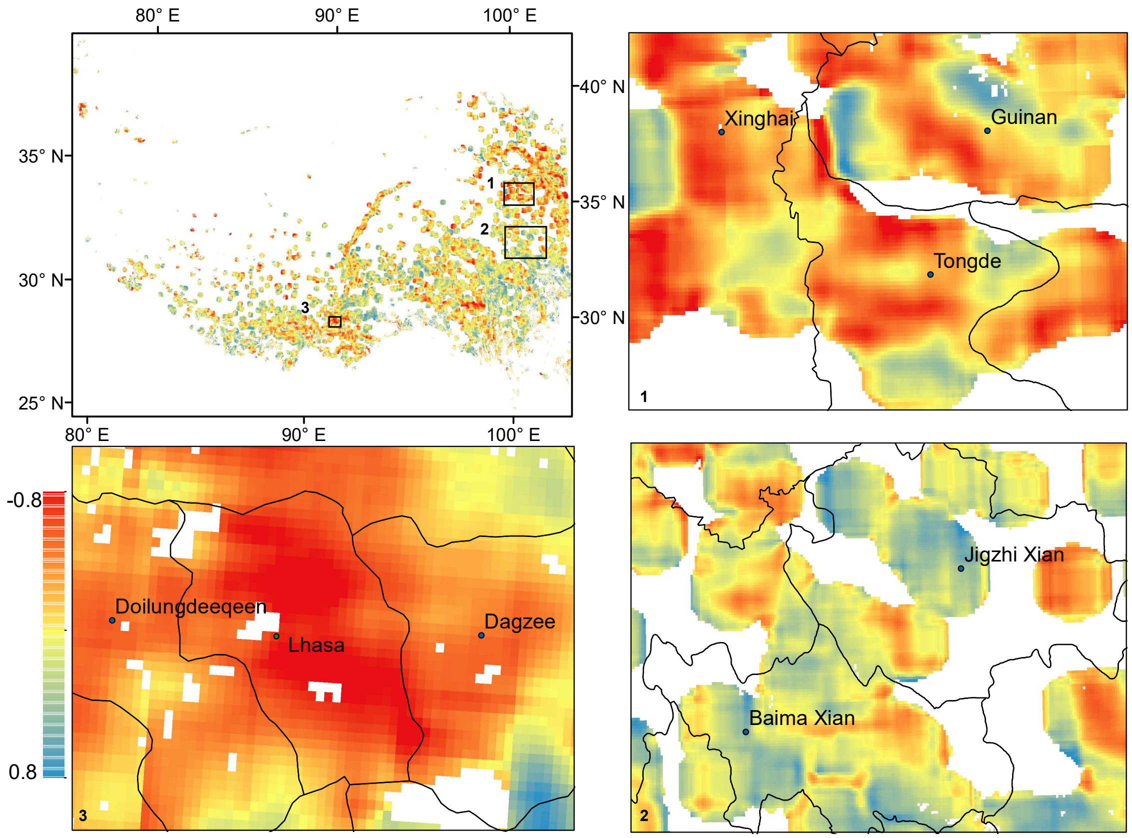

Figure 9. Scatterplot between human-influenced spatial biomass pattern at the 500 m scale (y) and livestock density at the 10 km scale (x). Note that a positive human-influenced spatial biomass pattern reflects a negative correlation between local biomass and distance to settlements, i.e. higher biomass close to settlements, and vise versa. The human-influenced spatial biomass pattern was averaged per county and then regressed on the livestock density per county. The dashed line indicates the division between positive and negative human influences on local biomass.